Aggregate Determinants of Food Production: A Preliminary Analysis with Implications for China

A Senior Honors Thesis

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Introduction:

With over 1.3 billion people, China has the largest population of any country[1], let alone a developing state. However, unlike many developing countries, China's population enjoys a good standard of living that is improving every day. Over 90% are literate, including 86.5% of women, and the average life expectancy is over 70 years. A well-educated society as well as government policy contributes to a birthrate of merely 1.75 children/woman[2].

With this population growth stabilization—thanks in large part to the government mandated One-Child Policy[3]—there still remains a rather large, well-educated consumer base with ever-improving quality of life and growing consumer potential. By the year 2025 the population will be over 1.45 billion[4], and the GDP has grown at an average of 7.3% per annum over the past 10 years (The only country that can be compared reasonably is India, and even then it only has $2,820 GDP per capita, a 5% GDP growth rate, and an estimated 2025 population of 1.3 billion)[1]. In fact, over the past thirty years the size of China's economy has doubled nearly three times over; the rate of China's economic growth has no equal in modern history[5]. Even more startling is its resiliency; defying standard economic prediction, the economy is not in any danger of succumbing to a bursting stock market bubble because the stock market is not a significant part of the economy in the first place[6]. The impact of inflation on exports has been mitigated through depreciation of the U.S. dollar, leaving the import-price index of Chinese goods

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1 WRI Tables (http://www.zippublishing.com/112files)
2 CIA Factbook (https://www.cia.gov/library/publications/the-world-factbook/geos/ch.html)
3 Dietrich, p. 3-4, 270.
4 Allen & Leppman, p. 146.
5 Fishman, p. 12.
6 "The Great Wall of Money" (http://www.economist.com/displayStory.cfm?story_id=9225696)

at virtually zero since 2003; in other words, Chinese products are as cheap as ever in spite of rising input costs, meaning that the Chinese economy's productivity is significantly improving[7]. Although the World Bank has recently recalculated PPP standards and determined that China's GDP is 40% smaller than previously estimated, China's economy will, if current rates of growth are sustained, overtake the United States as the world's largest economy within ten years[8].

Despite the miraculous industrial economic growth, agriculture is, and has always been, a large part of life in China. Before the Communist Revolution, 94% of the population consisted of rural, subsistence farmers, and even before the global population booms following the World Wars, China had about 25% of the global population living off only 6% of the world's arable land. In order to cultivate the same plots of land year-in and year-out to maintain its population, the Chinese over hundreds of years developed strong agricultural techniques akin to the Green Revolution such as crop rotation, selective seeding, fertilizers, and well-placed irrigation[9]. In addition to intensive practices, the Chinese have also invested in extensive practices; the total available percentage of arable land in China has increased from 10.4% in 1980 to 13.3% in 2000[10].

As such, even in modern times Chinese agriculture remains innovative, and such innovation with help from a long-standing tradition of utilizing grain reserves has allowed China to remain self-sufficient throughout its long history[11]. In fact, the supply growth for food calculated from WRI tables remains steady at just over 6% per annum.

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[7] "Smelling a rat," *The Economist*, The World in 2008: China Special Edition, p.52
[8] "Clipping the dragon's wings," *The Economist*, December 22, 2007-January 4, 2008, p. 68
[9] Dietrich, p. 12.
[10] Allen & Leppman, p. 165.
[11] "China Maintains Self-Sufficent in Food Supply" (http://english.people.com.cn/200309/23/eng20030923_124774.shtml)

Despite technological innovation and thrifty rationing, there remains a limit as to how much food can be produced at one time. The calculated demand growth for food is increasing with the population at steady rate of just over 8% per annum[1]. If current rates of supply and demand growth merely remain constant, there will come a point within the next fifty years where the demand for food will be greater than the capability of the Chinese to supply it, as shown in the graph:

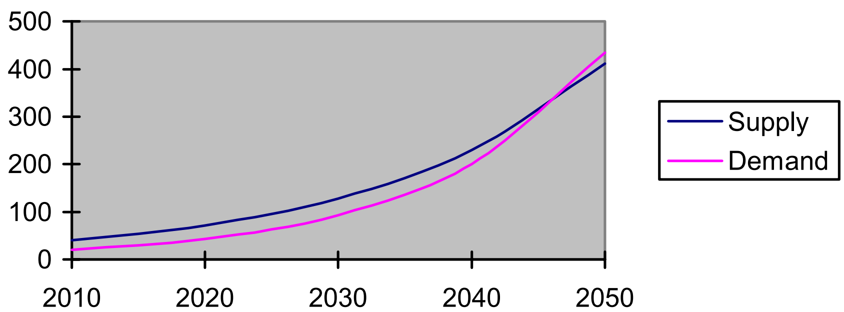

Figure 1: Where Demand Will Overtake Supply At Current Rates

When that point is reached, the largest consumer base in the world will have to rely on imported food for the first time in its history, and because that base is steadily gaining consumer power and is becoming more and more demanding on the variety of food in the diet in accordance with Bennett's Law, the global economy must brace itself for the impact it will face toward the end of the current generation's lifetime.

This situation is problematic enough while the rates remain constant; when environmental factors are weighed and the supply variables change, the situation becomes much more precarious. At first glance it might appear that the environment would be the least of China's worries; it has a net reforestation rate of 1.2% per annum and the per capita groundwater recharge is significantly greater than the per capita withdraw[12]. It also has outpaced the United States in curbing total carbon emissions, with total output reaching 92% of that of the U.S. by 2010[13]. When adding the extensification of arable land to the equation, the logical conclusion is that the environmental factors actually help China's food problem rather than hurt it. However, this data doesn't take into account all the consequences of industry. China's booming economy is fueled not by exports, but rather by investment in local infrastructure and property[14], meaning that industrial growth is prioritized even over agricultural production. To illustrate, only 9% of the available arable land (1.2% of the total land) is set aside permanently for crops[4], while at the same time China is experiencing an Industrial Growth Production Rate of 22.9% per annum[2]. This translates into more and more urban sprawl and polluting sources, including coal power plants (China is on track to produce 562 new plants at an average of one per week, which is about half of the total expected to be produced worldwide in the next eight years[15]). To make matters worse, soil erosion and other ecological downfalls are all side effects of attempts to modernize, all of which affect the total agricultural output[16]. In addition, many farmers are switching to produce cash crops rather than food staples[11], thus reducing the total food production even further.

In order to understand how the consequences of industry affect agricultural output, one must first understand the medium through which agriculture is derived: the soil. Soil is comprised of three primary layers: the A horizon or topsoil, which is dark and granular; the B horizon or subsoil, which is rocky and lighter in color, and the C horizon or parent material, which is primarily the clay that would mix with decomposing

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[12] Allen and Lippman, p. 165, 175.
[13] Clayton, "Is China Outdoing US in Curbing Carbon?"
[14] "Economics focus: An old Chinese myth," *The Economist*, January 5-11, 2008, p. 75
[15] Clayton, "New Coal Plants Bury 'Kyoto.'" (http://www.csmonitor.com/2004/1223/p01s04-sten.html)
[16] Dietrich, p. 329-331.

material known as tilth to create the topsoil. Individual particles of soil that build the architecture in each horizon are called soil aggregates. In healthy soil the architecture is spacious, allowing for roots to spread and breathe and for water to flow and drain[17].

When the soil is contaminated, this architecture is lost. The clay C horizon has a natural negative charge, whereas salt and metals in industrial sludges contain positive ions, and when the two meet they repel each other, resulting in a collapse and compacting of the soil aggregates that removes space for roots, water, and air. On top of this, the metals that accumulate act as herbicides, accruing within plants to a point where they will cease growing and die. Trace metals come from varying sources; copper derives from plumbing, and zinc, nickel, and lead come from sludge. All of these reach the soil through the water table[17].

Through examining the empirical evidence in the data, the nature in which trace metals affect plant growth, and my own first-hand observation of the situation in China, I arrive at the conclusion that water pollution could be having a significant impact on the supply of food, reducing the timeframe in which demand will overtake supply and thus force China to become a major food importer. This paper will serve as an exploration, a preliminary glimpse as to the extent of this impact. To compensate for the lack of reliable statistics at sub-national levels within China, a cross-sectional comparison between China and other countries in various states of environmental condition, economic growth, and agricultural capacity will be used to sample data on water pollution, soil quality, and agricultural output in order to perform a regression analysis. China's current status will be then be compared to the resulting function. This paper will conclude with implications and suggestions for future research.

[17] Interview with Dr. Karen Mancl, December 5, 2007

Defining Water Quality:

Unlike most scientifically measured parameters, it is difficult to form an adequate standard definition of water quality. The United States Geological Survey defines water quality as "a term used to describe the chemical, physical, and biological characteristics of water, usually in respect to its suitability for a particular purpose."[18] In other words, scientific measurements are only one part of what constitutes water quality; the other part is a value-based judgment derived from the context of the intended water use. For example: Water that is considered to be of good quality for fishing or boating may not be considered to be of good quality for bathing or drinking, as explained on the standard Water Quality Ladder which ranks water quality on a scale of 1-10 with varying rungs of the ladder noting the varying degrees of safety for water-related activities[19].

Even more difficult than defining water quality is constructing the proper context for its use, particularly when it comes to agriculture and food production. This is because agriculture and food production are considered at best to be part of a self-feeding cycle of water and environmental degradation—being "both cause and victim of water pollution"[20]—but more typically are considered to be primarily cause rather than victim as agricultural runoff is a major source of non-point pollution.[18] As a result, there is a scarcity of prior work examining the role of water quality for the context of food production.

In order to begin practical analysis of water quality in any context, there must be a consensus in the international community on a methodological approach to measuring it.

[18] USGS (http://ga.water.usgs.gov/edu/waterquality.html)
[19] Water Pollution Ladder and Value Levels (http://yosemite.epa.gov/ee/epa/hair.nsf/70c50f7ad4063ca18525677c0065897c/c933b36a6836a35d8525647a004c5040!OpenDocument)
[20] "Control of water pollution through agriculture" (http://www.fao.org/docrep/W2598E/w2598e04.htm)

While there is yet to be an ideal single-indicator water quality index, a consensus has been reached on the next-best approach. In August 2006 the Food and Agriculture Organization of the United Nations prepared a report on behalf of the UN-Water Task Force on Monitoring entitled "Mapping Existing Global Systems & Initiatives."[21] The purpose of this document was to outline the efforts of inter-agency information exchange and proper monitoring as well as highlight progress on reaching the United Nations' eight Millennium Development Goals.

The report mentions in detail the work of the Commission in Sustainable Development (CSD) to identify and standardize a set of 58 Indicators for Sustainable Development (ISD).[21] These 58 indicators are broken-down into a series of themes and sub-themes that each contain a grouping of core indicators that determine the proper unit of measurement for the particular theme. The theme of "freshwater" is divided into two sub-themes, "Water Quantity" and "Water Quality," meaning that a sustainable freshwater system should be defined not only in terms of the overall quality of the source, but also by how much is available. "Water Quantity" is denoted by one core indicator: "Annual Withdrawal of Ground and Surface as Percent of Total Water Renewable." "Water Quality" is denoted by two core indicators: "BOD in Water Bodies" and "Concentration of Faecal Coliform in Freshwater."[21]

However, in terms of agriculture, faecal coliform and BOD should not have much if any negative impact, as animal waste is often used as a fertilizer. Therefore, to include them would be, in effect, to double-count the effect of fertilizer in food production. Therefore neither BOD nor Faecal Coliform will be included in the analysis. Instead the

[21] "Mapping Global Systems & Initiatives" (http://www.fao.org/nr/water/docs/UNW_MONITORING_REPORT.pdf)

analysis will include common trace metals that are found in industrial sludges that make their way into the water table: copper and lead.

This paper will follow the guidelines provided in the FAO report and consider the appropriate methodological approach to be viewing the water parameter in terms of sustainability of water systems; in addition to defining water quality, the paper will also include water quantity to give appropriate context. It will define "water quantity" as "Agricultural Water Withdrawal as Part of Total," and it will define "water quality" as "Level of Copper in Water" and "Level of Lead in Water"

Measuring Food Production:

The standard metaproduction function for food used in the international community was proposed by *Zhao et al* in the *International Journal of Agricultural Economics*[22]. This metaproduction function measures the relationship between the rate of change of food output and the rate of change of food inputs.

This intent of this paper is to measure the relationship between aggregate food output and aggregate inputs; as such, *Zhao et al* cannot be directly used in that regard. Instead a new metaproduction function will be proposed replacing the flow variables (rates of change) in the *Zhao et al* function with their respective aggregate outputs.

Methodology:

This analysis is based on the metaproduction function proposed in *Zhao et al*. The *Zhao et al* metaproduction function is as follows[22]:

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[22] *Zhao et al*, "Impact and implications of price policy and land degradation on agricultural growth in developing countries." *International Journal of Agricultural* Economics, 1991, vol. 5, issue 4, p. 311-324.

$Yg = f(Ag, Lg, Q, Fg, Mg, G)$

Where,
Yg = Rate of Change of Food Production
Ag = Rate of Change in Labor, expected +
Lg = Rate of Change in Land Cropped, expected +
Q = Quality of Arable Land, i.e. Land Degradation, expected –
Fg = Rate of Change in Fertilizer Consumption, expected +
Mg = Rate of Change in Machinery Utilization, expected +
G = Government intervention, expected –

After adjusting for my hypothesis, the new metaproduction function is as follows:

$TFP = f(A, L, Q, F, M, G, W, Cu, P)$

Where,
TFP = Aggregate Food Production
A = Aggregate Labor, expected +
L = Aggregate Land Cropped, expected +
Q = Quality of Arable Land, i.e. Land Degradation, expected –
F = Aggregate Fertilizer Consumption, expected +
G = Government intervention, expected –
M = Aggregate Machinery Utilization, expected +
W = Agricultural Water Withdrawal, expected +
Cu = Level of Copper in Water, expected –
P = Level of Lead in Water, expected –

The theoretical speculation of the equation is:

$$E(TFP) = \beta_0 + \beta_1 \ln A - \beta_2 \ln L - \beta_3 Q + \beta_4 \ln F + \beta_5 \ln M - \beta_6 G_p - \beta_7 G_n + \beta_8 \ln W - \beta_9 Cu - \beta_{10} P$$

Land Cropped, Labor, Fertilizer, Machinery, and Water Withdrawal are all log variables because I expect diminishing marginal returns for their use; each one will have an optimum point of usage before additional amounts of each will become detrimental to production. Soil Quality and the levels of Copper and Lead are linear because in theory the greater each of these variables are, the more or less can be grown respectively. Government intervention is a dummy variable because the level of intervention can impact the results for everything else. The base equation is set assuming a Freedom House ranking of "Free." The first intercept is for a ranking of "Partly Free" ($\beta_6 G_p$), and the second is for a ranking of "Not Free" ($\beta_7 G_n$). While there is little formulaic estimation of the quality of extension services, intuition says that the more "Free" a nation is, the less restriction there will be on the flow of and access to information, and, therefore, the better the quality of, and access to, extension services will be. Ergo, each intercept will give some indication of the effectiveness of agricultural extension in addition to the impact of government intervention.

The sources of data and definitions for the variables are as follows:

The World Bank World Development Indicators (WDI Online):

TFP: Cereal Yield (kg/hectare)
Ag: % in Agriculture of Total Employment
Lg: % of Land Area that is Arable
Fg: Fertilizer Consumption (100g/hectare of arable land)
Mg: Agricultural Machinery (tractors per 100 sq. km. of arable land)

Other Sources:

G: Freedom House Ranking (www.freedomhouse.org)
Q: GLASOD Estimate of Total Land Degradation (www.isric.org)
W: Agricultural Water Withdrawal as % of Total (www.fao.org)
Cu, P: mg Cu/L, mg Pb/L (www.gemstat.org)

Each variable was measured as the average of the outputs for the period of 1998-2002. The sample size was 29 nations, primarily because the recorded data on water contaminants is so limited that these 29 nations were the only ones that had recent data for all the variables. Fortunately, these 29 nations are a mixture of nations from all continents, all stages of development, and all political structures, keeping bias to a reasonable minimum in that regard. The nations have GDP/Capita ranging from as low as $1,100 (Tanzania) to as high as $55,600 (Norway), with a mean GDP/Capita of

$19,513.80. Over 40% of the nations have a GDP/Capita less than $10,000, and just under 30% of the nations have a GDP/Capita between $10-30,000. The remaining 30% of the nations have a GDP/Capita over $30,000. This variation between low, medium, and high income nations indicates a good mixture of economic variation, which limits bias. However, it should be noted that none of the states are failing or on the verge of collapse, and all are above the $1-per-day poverty guideline[2].

In instances where data for a specific country for a specific variable were missing for a specific year in the selected period, data from the most recent previously available year were substituted. In most cases the lapses of yearly data in recorded databases were simply because that year was the same as the previous, but in some there were genuine gaps in data gathered and as such I had no choice but to include the most recent data as a substitute. This does indicate the potential for bias, but more importantly if the findings of the analysis are significant it calls for the international community to take a serious look at its efforts in monitoring environmental factors, not only so that more accurate tests may be done in the future but also that it would make it much easier to manage environmental externalities. The regression itself is a cross-sectional analysis performed on EViews. The list of the 29 nations and their corresponding input data are included in the supporting materials appendix of this paper.

Analysis of Regression Results:

For comparative purposes I first ran the data using the aggregates of the variables in the original *Zhao et al* function:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:06

Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-454.6461	237.7866	-1.911992	0.0696
LOG(L)	758.3299	382.7408	1.981314	0.0608
Q	-4599.487	2752.791	-1.670845	0.1096
LOG(F)	849.3804	247.6570	3.429665	0.0025
LOG(M)	13.97030	229.4741	0.060880	0.9520
GP	-26.78996	571.9966	-0.046836	0.9631
GN	-22.56620	766.3614	-0.029446	0.9768
C	-838.8397	1707.710	-0.491207	0.6284

R-squared	0.695280	Mean dependent var	3765.786
Adjusted R-squared	0.593707	S.D. dependent var	1739.977
S.E. of regression	1109.080	Akaike info criterion	17.08940
Sum squared resid	25831247	Schwarz criterion	17.46659
Log likelihood	-239.7963	Hannan-Quinn criter.	17.20753
F-statistic	6.845114	Durbin-Watson stat	2.204231
Prob(F-statistic)	0.000266		

Table 1

The results matched theory and expectations for all coefficients with the exception of labor being negative. While unexpected, this result makes sense within the context of diminishing marginal returns; nations that produce greater agriculture yield tend to have less of their labor force devoted to agriculture because of advances in technology, and as such more workers hinder efficiency. In other words, labor in the agricultural sector has already reached its efficiency maximum, and more labor would reduce production. The R-squared and Adjusted R-squared values are higher than the norm for cross-sectional analyses, indicating that the original function provides a good description for food production.

In examining the statistical readout, the output for “Q” has the highest standard deviation by far. This indicates that soil quality varies greatly among the nations, which the data supports. The highest absolute value of a t-statistic belongs to the fertilizer variable, indicating that fertilizer is statistically the most significant input for food production, which makes perfect sense. The next most significant inputs are labor, land, and soil quality, and the least significant inputs were machinery and government intervention. The F-statistic for the regression is above the critical value for significance at the 10%, 5%, and 2.5% levels, further supporting the explanatory value of the regression.

This being done, it was now time to run my hypothetical function, adding water quality variables:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:12
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-514.2266	261.9602	-1.962995	0.0653
LOG(L)	400.2586	457.6995	0.874501	0.3934
Q	-3205.945	2948.236	-1.087411	0.2912
LOG(F)	873.3721	264.6320	3.300327	0.0040
LOG(M)	-83.28509	245.3161	-0.339501	0.7382
GP	-306.8638	645.7123	-0.475233	0.6403
GN	-333.6050	815.4180	-0.409121	0.6873
LOG(W)	93.85795	334.3611	0.280708	0.7821
CU	-4554.830	4772.252	-0.954440	0.3525
P	-1531.316	1322.958	-1.157494	0.2622
C	-1163.228	1791.358	-0.649355	0.5243

R-squared	0.729756	Mean dependent var	3765.786
Adjusted R-squared	0.579621	S.D. dependent var	1739.977
S.E. of regression	1128.143	Akaike info criterion	17.17623
Sum squared resid	22908719	Schwarz criterion	17.69486
Log likelihood	-238.0553	Hannan-Quinn criter.	17.33866
F-statistic	4.860649	Durbin-Watson stat	2.410013
Prob(F-statistic)	0.001815		

Table 2

The good news in this run is that the coefficients all showed their expected signs. The bad news is that the Adjusted R-squared value and the F-statistic decreased from the original, indicating that at least one of the new water quality variables is not significant to food production Furthermore, in this run the t-statistics for the new variables are not indicative of significance. To investigate, I ran the function three more times only adding one of the new variables for each run, starting with Water Quantity:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:11
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-436.5843	253.6436	-1.721251	0.1006
LOG(L)	753.1118	392.1222	1.920605	0.0692
Q	-4552.559	2822.486	-1.612960	0.1224
LOG(F)	849.1975	253.3732	3.351568	0.0032
LOG(M)	3.835876	238.1997	0.016104	0.9873
GP	-4.323244	591.9693	-0.007303	0.9942
GN	-1.733251	788.4064	-0.002198	0.9983
LOG(W)	-79.01806	314.0425	-0.251616	0.8039
C	-832.8584	1747.280	-0.476660	0.6388

R-squared	0.696242	Mean dependent var	3765.786
Adjusted R-squared	0.574739	S.D. dependent var	1739.977
S.E. of regression	1134.675	Akaike info criterion	17.15521
Sum squared resid	25749735	Schwarz criterion	17.57954
Log likelihood	-239.7505	Hannan-Quinn criter.	17.28810
F-statistic	5.730232	Durbin-Watson stat	2.191750
Prob(F-statistic)	0.000728		

Table 3

Adjusted R-squared was the lowest yet, and being coupled with a very low t-statistic indicates that “Agricultural Water Withdrawal as a % of the Total” is not significant. It also indicates that at least one of the metals has a higher significance; if it didn’t then the run for the new function as a whole would be lower. Next I ran for copper:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:14
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-439.4079	238.4097	-1.843079	0.0802
LOG(L)	580.8695	422.9005	1.373537	0.1848
Q	-4075.099	2804.813	-1.452895	0.1618
LOG(F)	918.2046	257.3745	3.567582	0.0019
LOG(M)	-47.14972	237.7673	-0.198302	0.8448
GP	-8.313881	572.6013	-0.014519	0.9886
GN	-169.7912	781.0817	-0.217380	0.8301
CU	-4584.312	4635.591	-0.988938	0.3345
C	-1250.117	1758.489	-0.710904	0.4854

R-squared	0.709486	Mean dependent var	3765.786
Adjusted R-squared	0.593281	S.D. dependent var	1739.977
S.E. of regression	1109.662	Akaike info criterion	17.11062
Sum squared resid	24626989	Schwarz criterion	17.53496
Log likelihood	-239.1041	Hannan-Quinn criter.	17.24352
F-statistic	6.105449	Durbin-Watson stat	2.222161
Prob(F-statistic)	0.000490		

Table 4

Sure enough, the Adjusted R-squared is higher than the original function, however the t-statistic for copper showed little change, leaving the significance of copper temporarily inconclusive. Next I ran lead:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:17
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-505.4619	239.0849	-2.114152	0.0473
LOG(L)	579.0280	407.1003	1.422322	0.1703
Q	-3713.933	2822.116	-1.316010	0.2031
LOG(F)	806.8258	247.6281	3.258216	0.0039
LOG(M)	-32.36115	230.3391	-0.140494	0.8897
GP	-286.0311	605.7781	-0.472171	0.6419

GN	-156.1388	766.4986	-0.203704	0.8406
P	-1460.855	1215.868	-1.201491	0.2436
C	-751.6938	1691.510	-0.444392	0.6615

R-squared	0.715794	Mean dependent var	3765.786
Adjusted R-squared	0.602112	S.D. dependent var	1739.977
S.E. of regression	1097.549	Akaike info criterion	17.08867
Sum squared resid	24092288	Schwarz criterion	17.51301
Log likelihood	-238.7858	Hannan-Quinn criter.	17.22157
F-statistic	6.296437	Durbin-Watson stat	2.337635
Prob(F-statistic)	0.000402		

Table 5

The Adjusted R-squared is higher yet and lead shows a significant t-value, indicating that lead should have a negative significance. I ran it with both metals to make sure:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:18
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-489.2429	240.3304	-2.035710	0.0560
LOG(L)	416.7404	442.7771	0.941197	0.3584
Q	-3246.649	2872.396	-1.130293	0.2724
LOG(F)	873.6316	258.1355	3.384392	0.0031
LOG(M)	-88.78734	238.5302	-0.372227	0.7138
GP	-259.5496	608.0266	-0.426872	0.6743
GN	-291.2996	781.7013	-0.372648	0.7135
CU	-4352.108	4601.514	-0.945799	0.3561
P	-1410.470	1220.250	-1.155886	0.2621
C	-1145.145	1746.262	-0.655769	0.5198

R-squared	0.728573	Mean dependent var	3765.786
Adjusted R-squared	0.600002	S.D. dependent var	1739.977
S.E. of regression	1100.455	Akaike info criterion	17.11163
Sum squared resid	23009005	Schwarz criterion	17.58311
Log likelihood	-238.1187	Hannan-Quinn criter.	17.25929
F-statistic	5.666713	Durbin-Watson stat	2.369916
Prob(F-statistic)	0.000737		

Table 6

Two notes of interest arise in this case. The first is that the density of tractors on arable land over the past two runs has become a consistently negative coefficient. This can be explained through diminishing marginal returns; there's only so much machinery you can have out on a field before you get all the usefulness out of mechanization. More importantly, it has also shown a low t-statistic throughout each regression, indicating that either mechanization is not as significant to production as thought—which is unlikely—or rather that mechanization has a collinear relationship with labor; labor decreases as it becomes more efficient, and part of being more efficient involves the use of more capital, which in this case is agricultural machinery. Therefore, it is likely that the coefficient for labor is reflecting the use of tractors, which would explain why "M" has been testing poorly.

The second note of interest is that running for both metals combined results in a higher Adjusted R-squared value than the original function, but a lower value than running for lead alone. Both of their respective t-values are lower as well.

It became clear that I needed to go back to my background research to find an explanation. It didn't take long to do so, however: Copper is an herbicidal metal, but lead is not. Lead functions in plants much like it does in humans; it has no natural function but will bond within the plant molecules, not necessarily killing the plant but certainly posing a health risk to anyone consuming it[17]. Lead happens to be prevalent in industrial sludges, which would make it a good indicator of the presence of other plant toxins in the water, explaining why the presence of lead is more significant in the function on its own. Since copper is the actual herbicide, it also explains why running the function with both metals makes it less significant.

In order to test the validity of this explanation I decided to test the function for the presence of a third metal, zinc. I chose zinc because not only is it prevalent in sludges like lead, it is also an herbicide like copper. Zinc will be represented as the variable "Z," measured in mg Zn/L. For this and further comparative regressions, I left "M" in the equation even though it is likely insignificant. This was done so that the changes in the results would still be comparable to the regressions that had already used "M." I then tested the function adding just zinc:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:20
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-522.3562	240.3976	-2.172885	0.0420
LOG(L)	635.3444	389.5400	1.631012	0.1185
Q	-4015.937	2752.296	-1.459123	0.1601
LOG(F)	821.1743	245.1421	3.349789	0.0032
LOG(M)	-40.39280	230.2284	-0.175447	0.8625
GP	-237.0540	587.6925	-0.403364	0.6910
GN	-88.00197	757.2129	-0.116218	0.9086
Z	-264.7515	208.6080	-1.269134	0.2190
C	-726.5542	1685.731	-0.431003	0.6711

R-squared	0.717992	Mean dependent var	3765.786
Adjusted R-squared	0.605189	S.D. dependent var	1739.977
S.E. of regression	1093.297	Akaike info criterion	17.08091
Sum squared resid	23905977	Schwarz criterion	17.50524
Log likelihood	-238.6732	Hannan-Quinn criter.	17.21381
F-statistic	6.364992	Durbin-Watson stat	2.215802
Prob(F-statistic)	0.000375		

Table 6

The Adjusted R-squared value was its highest yet, and zinc shows a significant t-statistic. Next I ran zinc and lead together:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:25
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-520.5951	247.2390	-2.105635	0.0488
LOG(L)	620.1776	428.6669	1.446759	0.1643
Q	-3936.629	2937.517	-1.340121	0.1960
LOG(F)	817.3935	254.4089	3.212912	0.0046
LOG(M)	-40.14672	236.1635	-0.169995	0.8668
GP	-252.9984	624.5166	-0.405111	0.6899
GN	-104.1296	794.0434	-0.131138	0.8970
P	-308.3749	3156.914	-0.097682	0.9232
Z	-215.9229	543.7420	-0.397105	0.6957
C	-728.8674	1729.251	-0.421493	0.6781

R-squared	0.718133	Mean dependent var	3765.786
Adjusted R-squared	0.584618	S.D. dependent var	1739.977
S.E. of regression	1121.418	Akaike info criterion	17.14937
Sum squared resid	23893977	Schwarz criterion	17.62085
Log likelihood	-238.6659	Hannan-Quinn criter.	17.29704
F-statistic	5.378642	Durbin-Watson stat	2.242228
Prob(F-statistic)	0.001010		

Table 7

The Adjusted R-squared value drops considerably, as does the t-statistic for both metals.

Next I ran for zinc and copper:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:27
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-514.1316	237.3383	-2.166239	0.0432
LOG(L)	397.1306	429.8333	0.923918	0.3671
Q	-3277.628	2780.810	-1.178660	0.2531
LOG(F)	901.7001	250.5064	3.599509	0.0019
LOG(M)	-124.3131	237.0913	-0.524326	0.6061
GP	-247.1084	580.0434	-0.426017	0.6749
GN	-279.9111	763.1690	-0.366775	0.7178
CU	-5657.315	4566.241	-1.238943	0.2305

Z	-306.1205	208.5629	-1.467761	0.1585
C	-1216.550	1709.992	-0.711436	0.4855

R-squared	0.739072	Mean dependent var	3765.786
Adjusted R-squared	0.615474	S.D. dependent var	1739.977
S.E. of regression	1078.962	Akaike info criterion	17.07218
Sum squared resid	22119016	Schwarz criterion	17.54367
Log likelihood	-237.5467	Hannan-Quinn criter.	17.21985
F-statistic	5.979664	Durbin-Watson stat	2.275784
Prob(F-statistic)	0.000529		

Table 8

Both the R-squared and Adjusted R-squared values are the highest of any of the regressions run thus far, and the t-statistics for the metals are at significant levels.

Finally, I checked for all three metals together:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:29
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-523.5473	242.2169	-2.161481	0.0444
LOG(L)	433.8498	442.3392	0.980808	0.3397
Q	-3604.122	2888.395	-1.247794	0.2281
LOG(F)	947.9417	267.5750	3.542713	0.0023
LOG(M)	-148.1796	244.9862	-0.604849	0.5528
GP	-144.7870	617.1061	-0.234623	0.8171
GN	-224.5901	783.0532	-0.286813	0.7775
CU	-7156.995	5337.930	-1.340781	0.1967
P	2030.511	3550.712	0.571860	0.5745
Z	-638.6012	618.9701	-1.031716	0.3159
C	-1331.210	1752.611	-0.759558	0.4574

R-squared	0.743728	Mean dependent var	3765.786
Adjusted R-squared	0.601354	S.D. dependent var	1739.977
S.E. of regression	1098.593	Akaike info criterion	17.12315
Sum squared resid	21724328	Schwarz criterion	17.64177
Log likelihood	-237.2856	Hannan-Quinn criter.	17.28557
F-statistic	5.223782	Durbin-Watson stat	2.113210
Prob(F-statistic)	0.001201		

Table 9

The Adjusted R-squared value drops to lower than running it with zinc alone, and lead produces a low t-statistic. This leads me to conclude that what is significant isn't metals in general, rather herbicidal metals that make their way into the water supply.

Running the regression with "Agricultural Water Withdrawal as a % of Total" does not lead me to believe that Water Quantity is a significant factor in food production or in evaluating Water Quality for econometric purposes—directly contradicting the UN Millennium Development Goals consensus. However, just to make sure that I could be firm in my belief that Water Quantity isn't relevant in practice, I decided to run the regression switching out Water Withdrawal with Irrigation (% of cropland irrigated, represented by the variable "Irr"). If the level of irrigation proves to be insignificant, then it would be reasonable to infer that Water Quantity is insignificant. I started with the regression in Table 2, replacing "W" with "Irr":

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:34
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-522.8475	246.9607	-2.117128	0.0484
LOG(L)	374.5559	451.1075	0.830303	0.4172
Q	-3028.318	2918.453	-1.037645	0.3132
LOG(F)	796.4381	279.8984	2.845454	0.0107
LOG(M)	-110.7354	242.8953	-0.455898	0.6539
GP	-281.5353	615.4788	-0.457425	0.6528
GN	-545.8847	857.8265	-0.636358	0.5326
LOG(IRR)	164.0964	214.8524	0.763764	0.4549
CU	-4912.918	4710.397	-1.042994	0.3108
P	-1596.708	1257.718	-1.269527	0.2204
C	-246.6672	2121.715	-0.116258	0.9087

R-squared	0.737093	Mean dependent var	3765.786
Adjusted R-squared	0.591034	S.D. dependent var	1739.977

S.E. of regression	1112.723	Akaike info criterion	17.14870
Sum squared resid	22286747	Schwarz criterion	17.66733
Log likelihood	-237.6562	Hannan-Quinn criter.	17.31113
F-statistic	5.046533	Durbin-Watson stat	2.427094
Prob(F-statistic)	0.001466		

Table 10

The Adjusted R-squared value is slightly higher than the run with Water Withdrawal, but lower that the run with only copper and zinc. The t-value, while higher that "W," is also relatively low. This means that Irrigation is also lowering the significance. Just to make sure, I ran it again replacing lead with zinc:

Dependent Variable: TFP
Method: Least Squares
Date: 04/01/08 Time: 16:37
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-539.0270	244.0559	-2.208621	0.0404
LOG(L)	373.7901	437.9953	0.853411	0.4046
Q	-3159.908	2829.875	-1.116625	0.2788
LOG(F)	842.3297	270.3094	3.116168	0.0060
LOG(M)	-140.5756	242.0767	-0.580707	0.5686
GP	-246.2382	589.0688	-0.418013	0.6809
GN	-480.4388	834.2065	-0.575923	0.5718
LOG(IRR)	135.2963	208.1874	0.649878	0.5240
CU	-6182.513	4707.172	-1.313424	0.2055
Z	-316.8294	212.4476	-1.491330	0.1532
C	-486.0150	2068.668	-0.234941	0.8169

R-squared	0.745054	Mean dependent var	3765.786
Adjusted R-squared	0.603417	S.D. dependent var	1739.977
S.E. of regression	1095.748	Akaike info criterion	17.11796
Sum squared resid	21611927	Schwarz criterion	17.63659
Log likelihood	-237.2104	Hannan-Quinn criter.	17.28039
F-statistic	5.260312	Durbin-Watson stat	2.312164
Prob(F-statistic)	0.001153		

Table 11

Again, introducing Irrigation makes the Adjusted R-squared value lower than with copper and zinc alone, and the t-value of "Irr" drops considerably.

Because the possibility of contradicting a UN consensus requires rigorous checks for possible counterexamples, I decided to run one more series of regressions with a water quantity variable, this time being the aggregate Water Withdrawal devoted to Agriculture (represented by the variable "aggw," measured in 10^9 m^3/yr). I first ran the regression from Table 2, substituting in "aggw" for "W":

Dependent Variable: TFP
Method: Least Squares
Date: 05/09/08 Time: 15:51
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-502.4455	247.0506	-2.033775	0.0570
LOG(L)	384.8535	457.2906	0.841595	0.4111
Q	-3163.416	2938.755	-1.076448	0.2959
LOG(F)	849.3761	268.6722	3.161385	0.0054
LOG(M)	-67.35664	247.8692	-0.271743	0.7889
LOG(AGGW)	61.89493	132.4107	0.467446	0.6458
GP	-341.7617	645.3578	-0.529569	0.6029
GN	-413.6356	840.0960	-0.492367	0.6284
CU	-4222.515	4707.342	-0.897006	0.3816
P	-1539.060	1276.149	-1.206019	0.2434
C	-1308.744	1817.340	-0.720142	0.4807

R-squared	0.731828	Mean dependent var	3765.786
Adjusted R-squared	0.582844	S.D. dependent var	1739.977
S.E. of regression	1123.809	Akaike info criterion	17.16853
Sum squared resid	22733043	Schwarz criterion	17.68716
Log likelihood	-237.9437	Hannan-Quinn criter.	17.33096
F-statistic	4.912121	Durbin-Watson stat	2.358353
Prob(F-statistic)	0.001710		

Table 12

The Adjusted R-squared value and the t-statistic for "aggw" are greater than their counterparts in the regression shown in Table 2, but less than that of their counterparts in the regression shown in Table 10, indicating that, while a better indicator than "W," it still is not significant. Again, I ran it replacing Zinc for Copper to be sure:

Dependent Variable: TFP
Method: Least Squares
Date: 05/09/08 Time: 16:00
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-526.1828	243.8961	-2.157406	0.0447
LOG(L)	371.6230	442.6623	0.839518	0.4122
Q	-3229.006	2842.743	-1.135877	0.2709
LOG(F)	881.7770	259.6262	3.396333	0.0032
LOG(M)	-104.4919	246.0895	-0.424609	0.6762
LOG(AGGW)	58.44812	128.5025	0.454840	0.6547
GP	-315.4941	611.3200	-0.516087	0.6121
GN	-390.6831	816.7682	-0.478328	0.6382
CU	-5610.561	4665.770	-1.202494	0.2448
Z	-321.9921	215.8958	-1.491423	0.1532
C	-1378.335	1782.686	-0.773179	0.4495

R-squared	0.742037	Mean dependent var	3765.786
Adjusted R-squared	0.598724	S.D. dependent var	1739.977
S.E. of regression	1102.212	Akaike info criterion	17.12972
Sum squared resid	21867684	Schwarz criterion	17.64835
Log likelihood	-237.3810	Hannan-Quinn criter.	17.29215
F-statistic	5.177737	Durbin-Watson stat	2.255639
Prob(F-statistic)	0.001264		

Table 13

Again, the Adjusted R-squared value and t-statistic are lower than that of the regression with "Irr" shown in Table 11. After this test I stand by my conclusion that Water Quantity is not a significant characteristic of Water Quality, meaning that the consensus definition put forth in the Millennium Development Goals was not an appropriate framework in this context.

Furthermore, there were only four inputs that consistantly demonstrated significance throughout all the regressions: Labor, Land, Soil Quality, and Fertilizer. I ran a regression using only these inputs:

Dependent Variable: TFP
Method: Least Squares
Date: 05/06/08 Time: 12:31

Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-463.8740	191.2618	-2.425335	0.0232
LOG(L)	773.3936	302.4402	2.557179	0.0173
Q	-4647.538	2488.863	-1.867333	0.0741
LOG(F)	859.1516	177.0645	4.852196	0.0001
C	-821.5246	1577.402	-0.520809	0.6073

R-squared	0.695184	Mean dependent var	3765.786
Adjusted R-squared	0.644381	S.D. dependent var	1739.977
S.E. of regression	1037.614	Akaike info criterion	16.88282
Sum squared resid	25839452	Schwarz criterion	17.11856
Log likelihood	-239.8009	Hannan-Quinn criter.	16.95665
F-statistic	13.68398	Durbin-Watson stat	2.206904
Prob(F-statistic)	0.000006		

Table 14

The Adjusted R-squared value is the higher than any of the other regressions, as are the t-values for the independent variables. To compare, I ran the regression once more adding the optimal metal combination of copper and zinc:

Dependent Variable: TFP
Method: Least Squares
Date: 05/06/08 Time: 12:34
Sample: 1 29
Included observations: 29

	Coefficient	Std. Error	t-Statistic	Prob.
LOG(A)	-493.1181	192.7236	-2.558680	0.0179
LOG(L)	439.1031	366.9612	1.196593	0.2442
Q	-3642.581	2509.497	-1.451518	0.1607
LOG(F)	823.6649	178.4782	4.614932	0.0001
CU	-4833.512	4047.901	-1.194079	0.2452
Z	-261.2365	184.3057	-1.417409	0.1704
C	-1262.090	1602.678	-0.787488	0.4394

R-squared	0.732749	Mean dependent var	3765.786
Adjusted R-squared	0.659863	S.D. dependent var	1739.977
S.E. of regression	1014.777	Akaike info criterion	16.88923
Sum squared resid	22654990	Schwarz criterion	17.21927
Log likelihood	-237.8938	Hannan-Quinn criter.	16.99259
F-statistic	10.05328	Durbin-Watson stat	2.250766

Prob(F-statistic)	0.000022

Table 15

The Adjusted R-squared value increases, and while the t-values of the non-metal inputs decrease (labor markedly so), they all remain at a significant level.

As explained in a later section of this paper, varying reasons from small sample size to unavailability of data render the results of this analysis inconclusive. That being the case, there are still several notes of interest that should be further explored. Because of the relationship between aggregate output and aggregate inputs, the *Zhao et al* metaproduction function may be due for a revision to remove machinery and government as well asa include Water Contaminants (metals with herbicidal properties) as proxies for Water Quality, as average rates of change should hold a similar relationship with average aggregates. In addition, a new metaproduction function to explain aggregate food production could possibly be in order:

$$TFP = f(A, L, Q, F, C)$$

Where,
TFP = Total Food Production
A = Aggregate Labor
L = Aggregate Land Cropped
Q = Quality of Arable Land
F = Aggregate Fertilizer Consumption
C = Concentration of Herbicidal Metals in the Water Supply

Furthermore, I conclude that these preliminary findings warrant a genuine need for the international community to begin serious efforts in monitoring the criteria set forth in the UN Millennium Development Goals; the current mindset is that, while they are a good benchmark, there are no plans to begin serious monitoring or data extraction as a result of these goals. The possibility raised from this analysis that water contaminants are negatively impacting food security should serve as a warning that pollution could be negatively impacting global food supplies at a much faster pace than global warming or population growth. Without proper monitoring, there will be not only no way to tell for sure, but also no way to act in time to prevent further damage. The international community must therefore immediately begin a substantial effort to gather data for the Millennium Development Goals.

Implications for China

The primary implication these results have for China is that forecasting of current trends will not provide the best timeframe for when food demand will outpace food supply; current trends do not account for the buildup of industrial pollution and water contaminants. If the industrial growth rate continues at its current level and the externalities that result are not prevented or abated, the resulting concentration of trace metals will likely greatly decrease the capacity to supply food, conceivably bringing the time that China will need to begin importing food staples to somewhere within the next 20-30 years instead of the next 50 years, if not sooner. However, if China begins a serious effort to improve environmental quality, it will not only prevent the decrease in food supply, it will also considerably delay the onset of the need to import food.

In theory the model reinforces this. The optimal regression (Table 15) results in the following function:

$$E(TFP) = -1262.09 - 493.1181(\ln A) + 439.1031(\ln L) - 3642.581(Q) + 823.6649(\ln F) - 4833.512(Cu) - 261.2365(Z) \pm e_i$$

When specifying for China, the function looks as follows:

$$TFP_{China} = -1262.09 - 493.1181(\ln(.458)) + 439.1031(\ln(.11)) - 3642.581(.3055) + 823.6649(\ln(3509.2)) - 4833.512(.00839) - 261.2365(.03684) \pm e_{China}$$

$TFP_{China} = 3714.466864 \pm e_{China}$; $e_{China} = 1155.333136$ ($TFP_{China\ Observed} = 4869.8$)

The following is, according to the model, what Total Food Production would have been if there were no trace metals in the water supply:

$$TFP_{China} = -1262.09 - 493.1181(\ln(.458)) + 439.1031(\ln(.11)) - 3642.581(.3055) + 823.6649(\ln(3509.2)) - 4833.512(0) - 261.2365(0) \pm e_{China} = 3764.643983$$

Without water contamination, the model indicates China could have been producing approximately 50 kg/hectare more in cereal yield per year over that 5-year period. That might not seem like much, but considering the size and scope of Chinese agriculture (86989660.8 hectares/year in that 5-year period), it indicates that China has potentially lost 4,364,890,538 kg of cereal yield per year for those 5 years, losing a total of 21,824,452,690 kg. In other words, from 1998-2002, water contamination may have cost China over 21 billion kilograms of food.

Imagine merely extending figures in this hypothetical situation from 2002 to present day. Imagine then extending the figures back from 1998 to the mid-70s when China first began its unprecedented industrial and economic growth. The deadweight loss in food production that China has accrued is potentially enormous. China will never have those years back; it can only look to the future when determining how to approach feeding its people.

Limitations and Suggestions for Future Research

Though yielding some revealing findings, the limitations of the analysis render the overall results inconclusive. The biggest limitation has been the lack of available data on the country level. If it were to be done again the analysis would be better served by obtaining more data from firsthand rather than secondhand sources. This would not only increase the accuracy of the results but also the sample of nations with which to analyze; even though the nations used were as diverse as possible under the constraints, at 29 the sample of nations is too small to significantly reflect processes on a global scale.

Another possible approach would be to do a panel analysis—a combination cross-sectional and time-series analysis—on China using data at the provincial level. This has the benefit of producing a clearer picture of the effects of inputs, as data on a smaller unit of division would more accurately reflect the impact of inputs per region as opposed to a national average or sum. It would also have the added benefit of reducing bias from lagged inputs while providing a more accurate description of changes in production over time. One problem with this approach is that even if data were readily available from China at the provincial level, there is a good possibility that it could be skewed to be more favorable for the Chinese government. A possible solution would be to choose another country, such as the United States, that has data at the provincial level (or the state level as this case is) that is not only readily accessible, but also relatively free from the risk of government manipulation. An area of concern with this approach is that potentially influential factors, such as the quality of extension services and selective seeding, that would normally be reflected in the error term or other independent variables on a multi-national analysis would not necessarily translate from one nation to another in an analysis on the provincial level, meaning that factors within the United States could impact the relationship between inputs and outputs in a manner that factors within China would not.

This concern aside, performing the analysis at the provincial level would allow for a wider range of variables to be tested; measures of hectares and measures of total employed in agriculture could be substituted for the percentages of land and labor devoted to agriculture, other measures of industrial output could be substituted for levels of trace metals in the water supply, and other measures of government investment or intervention could be substituted for a Freedom House ranking, since oftentimes data that is not available on the country level is more readily accessible on the provincial level. With other potential measures to test, it will be easier to determine which factors will produce statistically significant coefficients as well as the level of collinearity in the independent variables, which would produce more conclusive results.

Sample Nations and Data

Country	TFP	A	L	F	M	Gp	Gn
Argentina	3392.6	0.01	0.1	292.6	108.2	1	0
Australia	1926.8	0.048	0.06	493	67.4	0	0
Brazil	2791	0.226	0.07	1127.2	138.8	1	0
Canada	2700.4	0.034	0.05	562.6	158.8	0	0
China	4869.8	0.458	0.11	3509.2	83.2	0	1
Columbia	3245.2	0.09	0.022	2531.2	84.2	1	0
Cuba	2631.4	0.24	0.3	474.2	237.4	0	1
Germany	6558.8	0.028	0.34	2355.2	843.4	0	0
Ghana	1295	0.578	0.174	52	9	0	0
Hungary	4348.4	0.066	0.522	929.2	224.2	0	0
Indonesia	3991.6	0.446	0.112	1303	45	1	0
Japan	6051.8	0.05	0.12	3104.2	4613.6	0	0
S. Korea	6308	0.108	0.17	4572.2	1101.6	0	0
Malaysia	3033.8	0.17	0.056	6928.6	239.2	1	0
Mexico	2779.8	0.184	0.13	724.4	130.8	0	0
Netherlands	7444.2	0.03	0.27	4672.8	1654.8	0	0
New Zealand	6328.4	0.088	0.06	5194	499.8	0	0
Norway	3779.8	0.042	0.03	2143	1502	0	0
Pakistan	2262.6	0.464	0.28	1335	149.8	0	1
Peru	3113.4	0.056	0.03	714.4	36	0	0
Phillipines	2537	0.378	0.19	1279.8	20.4	0	0
Poland	2972.4	0.188	0.45	1129.2	853.2	0	0
Portugal	2856.6	0.128	0.196	1257.6	941.6	0	0
Spain	3151.8	0.068	0.266	1682.2	679.6	0	0
Tanzania	1372	0.832	0.046	46.4	19.4	1	0
Thailand	2651	0.478	0.31	1051	138.8	0	0
Turkey	2222.2	0.38	0.314	820.2	389.4	1	0
United Kingdom	6847.8	0.016	0.242	3225	849	0	0
United States	5744.2	0.026	0.19	1104.4	266	0	0

Country	Q	W	Cu	P	Irrigation	Zinc	Agg. Wthdrl.	GDP/Capita
Argentina	0.2349	0.74	0.0033	0.00308	0.05	0.04083	21.5	13000
Australia	0.1286	0.753	0.00671	1	0.05	6	18	37500
Brazil	0.1597	0.618	0.04001	0.0211	0.04	0.07774	36.6	9700
Canada	0.0121	0.118	0.004	0.004	0.016	0.16667	5.41	38200
China	0.3055	0.677	0.00839	0.002	0.472	0.002	427	5300
Columbia	0.1206	0.459	0.13517	0	0.216	0.03684	4.92	7200
Cuba	0.2506	0.688	0.002	0.001	0.212	0.002	5.64	4500
Germany	0.2414	0.198	0.00618	0.00548	0.04	0.0666	9.31	34400
Ghana	0.1121	0.664	0.04222	0.04089	0.006	0.18556	0.652	1400
Hungary	0.4093	0.321	0.005	0.00823	0.046	0.03238	2.45	19500
Indonesia	0.1653	0.913	0.02	0.05	0.134	0.02122	75.6	3400
Japan	0.014	0.625	0.00857	0.005	0.55	0.01612	55.2	33800
S. Korea	0.2659	0.48	0.01061	0.02	0.464	0.02069	8.92	24600
Malaysia	0.1678	0.627	0.214	0.03909	0.05	0.04971	5.6	14400
Mexico	0.1851	0.771	0.10333	0.0246	0.23	0.05	60.3	12500
Netherlands	0.1178	0.339	0.00215	0.00096	0.6	0.00863	2.69	38600
New Zealand	0.1748	0.422	0.015	0.005	0.086	0.007	0.89	27300
Norway	0.0282	0.105	0.00788	0.0017	0.04	0.00788	0.23	55600
Pakistan	0.3007	0.96	0.01801	0	0.814	0	163	2600
Peru	0.1383	0.816	0.22615	0.44692	0.28	1.06308	16.4	7600
Phillipines	0.1757	0.74	0.022	0.07667	0.146	0.07	21.1	3300
Poland	0.431	0.0833	0.00219	0.003	0.01	0.01501	1.35	16200
Portugal	0.3046	0.782	0.05	0.3	0.258	0.05	8.81	21800
Spain	0.2182	0.68	0.00462	0.00285	0.204	0.02169	4.63	33700
Tanzania	0.1337	0.894	0.06	0.11	0.032	0	24.2	1100
Thailand	0.3975	0.95	0.00744	0.01944	0.258	0.28294	82.8	8000
Turkey	0.3655	0.743	0.01843	0.019	0.18	0.04014	27.9	9400
United Kingdom	0.1164	0.0294	0.00508	0.00224	0.03	0.0146	0.28	35300
United States	0.0933	0.413	0.00156	0.001	0.13	0.00222	198	46000

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